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Modeling Academic Performance of The Students by using Partial Least Square

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Abstract: ***This study aims to model the relationship between predictor variables consisting of learning motivation (LM), parents' socioeconomic status (SS), and school environment (SE) which are all latent variables to academic achievement (AC) which are not latent variables. Modeling is done by the method of partial least square (PLS) which is expected to explore the various effects found in the inner model and also confirm the questionnaire items forming the latent variables. With a real level of 5%, almost all loading values on each latent variable are significant. Likewise, a simple linear relationship consisting of 5 models has a coefficient that has a significant effect. The influence of learning motivation (LM), parents' socioeconomic status (SS), school environment (SE) on academic achievement are 0.270, 0.249, and 0.320, respectively. while learning motivation (LM), socioeconomic status of parents (SS) contributing to academic achievement (AC) were 17.7% and 3.13%, respectively..***

Keywords **:** ***Academic performance, indirect effect, latent variable, modeling real problem.***

I. INTRODUCTION

The existence of various selection paths to enter state universities in Indonesia has led to very high variations in student abilities which are very intelligent students will be found and vice versa there will also be students who are not very smart academically. This condition is accompanied by the development of the area around the campus as a business and entertainment center. Many shopping and entertainment venues that are regarded by state universities students are a market segment due to the fact that many students come from middle and upper economic status. In addition, state universities have students who also come from all corners of the country from remote villages to the capital city, this has led to the emergence of rapidly growing primordial and religious groups.

The main mission of students is an academic achievement needed to be questioned. As an illustration of a case in the Beawijaya University, the faculty of computer science in Malang Indonesia. The facts show that many students have not graduated until the 7th year (maximum time limit for undergraduate programs). In 2019 there were 200 students, in 2018 there were 150 students, in 2017 there were 150 students, and in 2016 there were 120 students. It shows that there are still obstacles to being able to graduate on time. Of course, this obstacle comes from both sides in terms of study programs concerning the system and management of academic administration, as well as in terms of students and the environment around the campus.

The large of students' capacities around the state university campus have the emergence of many business people who take advantage of these potential market opportunities. Some business sectors that develop around the campus environment include business related to education, housing, entertainment, food, and leisure sectors in which business activities form an environmental factor that greatly influences the lifestyle of students. In the end, it will affect the success of student studies.

Several associational studies investigating the factors that significantly influence the success of student studies include Dennis et al [1], Lepp et al [2], Muhdin [3], and Singh et al [4]. The model used in their research is a linear regression that is looking for a relationship between predictor variables and response variables which both have a causal relationship and also the value of each variable can be observed directly. The variables involved are observed variables.

Research investigating the influence of several environmental factors which are latent variables on the success of learning achievement has been carried out by Kizito et al [5], Gajghat et al [6], and Ernawati [7]. They look to measure environmental factors to use indicators which reflect that factor or indicator that construct a factor. After the data is obtained by direct survey, to obtain the observed value of a factor is done by adding the values of the constituent indicators. Then the relationship model between latent variables is modeled by multivariable regression.

Multivariable regression modeling based on ordinary least square (OLS) optimization technique which has an objective function in the form of the sum of the squares of errors. By using the concept of the first partial derivative of the objective function of each of its parameters, the analytical solution of the parameter estimator that minimizes errors can be obtained. This OLS method has also been proven to be applied in fuzzy modeling systems as in Handoyo and Marji [8], Handoyo and Kusdarwati [9],

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Handoyo and Achmad [10]. Modeling the transfer function using OLS was done by Kusdarwati and Handoyo [11] and also on the time series modeling based on OLS optimization was conducted by Widodo et al [12]. The performance of the OLS method is also compared with the evolutionary computational method known as particle swarm optimization (PSO) which has been investigated by Handoyo et al [13], and also by Achmad et al [14]. Based on the above studies the OLS method has a very satisfying performance even comparable to the performance of the evolutionary method of the PSO.

Research with an instrument design involving latent variables such as that conducted by Ernawati {7] is not appropriate when it is analyzed by OLS-based multiple regression because it oversimplifies the problem and the information obtained is very minimum and is also doubtful because of the assumption of error normality is not met. Relationship associations between latent variables form a structured system of equations known as structural equation models (SEM) that are formed from a combination of regression models and path analysis. SEM also explores the contribution of an indicator to its latent variables and one of kind parameter estimation methods is the partial least square (PLS) algorithm [15]. The PLS algorithm is an iterative computation that can accommodate both reflective and formative latent variables [16]. Based on the description above in this article investigated the factors that influence student academic achievement, both directly and indirectly, and also explored the contribution of an indicator to its latent variable.

II. LITERATURE REVIEW

There have been many studies to determine student performance with different factors, including Research conducted by Dennis et al. [1], for 100 first-year ethnic minority students, the influencing factor was the presence of personal / career motivational events and friend support. Research conducted by Lepp et al. [2] resulted that cell phone use has a negative effect on IP and a positive effect on anxiety. Research conducted by Hussen [3] Factors that affect student academic performance is university entrance examination scores, sleep time and study habits. Other studies conducted by. Singh et al. [4], factors that have a significant positive effect are learning facilities, communication skills and guidance from parents.

Literature review was also carried out by Gajghat [6], in full as follows: factors that have significant influence include financial conditions, campus location, parent education, ability to manage time, self-motivation, self-discipline, desire to learn, effort / hard work, accommodation during study, time for cell phones / internet, career goals, college interests, extra activities, gender, ethnicity, age, text anxiety, length of sleep, mental health, happiness, stress, parental guidance, family support, mother's age, dedication & commitment, number of families, math scores in grade 12, high school UAN scores, entrance examination scores, knowledge of majors already held, academic abilities, activeness during class discussions, teaching quality, learning environment, lecturer attitude, faculty interaction and students, class attendance, teacher job satisfaction, peer support, campus distance, distractions, crowded lecture halls, lecture rules, study habits, student essay assignment. Research conducted by Ernawati [7] on the factors of Learning Motivation, Parents' Socio-Economic Status, and School Environment Against Learning Achievement using multivariable linear regression..

A. Partial Least Square Modeling

Partial Least Square (PLS) was first developed by Herman Wold in 1975. PLS can be used at any type of data scale (nominal, ordinal, interval, and ratio), does not assume the data must follow certain distributions, and the sample size is flexible. Therefore, PLS is called a powerful analysis method. PLS is an alternative used to explore the relationship between variables on the basis of weak model design theory. The PLS approach with a weak or non-existent theoretical foundation is more appropriate to be used for predictive purposes. Latent variables in the form of a linear combination of indicators can facilitate the acquisition of predictions from the value of latent variables. In addition, PLS can be used to confirm theories / test hypotheses [15].

The use of PLS is quite popular among researchers, for several reasons as follows [16]:

a. PLS algorithm is not limited to the relationship between indicators and reflective latent constituents, but also to formative relationships.
b. PLS can be used to estimate the path of the model with a small sample size.
c. PLS can be used for very complex models (many latent and manifest variables) without experiencing problems in estimating data.
d. PLS can be used when the data distribution is tilted.

B. Structural model (inner model) and measurement model (outer model)

The design of the relationship between latent variables is based on the formulation of the problem or research hypothesis. The basis for designing structural models in PLS includes theory (if available), empirical research results (concepts), analogies (relationships between variables with other fields), normative (for example, government regulations, laws, etc.), rational (premises) . Therefore, in PLS it is possible to explore relationships between latent variables so that they can use the premises as the basis for designing structural models and tested in the form of propositions.

The design of the measurement model in PLS is concerned with determining the indicator properties of each latent, reflective or formative variable. In determining the measurement model, if an error occurs it will produce an analysis with a low level of truth. Determination of the nature of the indicator is based on theory, prior empirical research, and rational thinking. However, references in the form of theory or previous empirical research are rarely found.

So that it can refer to the conceptual and operational definition of the variable to determine the nature of the indicator [15].

C. Model Parameters Estimation

In PLS, the algorithm for determining the weights, cross coefficients, and the value of latent variables in PLS is:

Stage 1. The iteration process begins by determining the values for outer weights through initializing all the values into one.

$$\tilde{w}_1 = (\tilde{w}_{11} = 1; \tilde{w}_{12} = 1; \tilde{w}_{13} = 1)$$
$$\tilde{w}_2 = (\tilde{w}_{21} = 1; \tilde{w}_{22} = 1; \tilde{w}_{23} = 1)$$
$$\tilde{w}_3 = (\tilde{w}_{31} = 1; \tilde{w}_{32} = 1; \tilde{w}_{33} = 1) \qquad (1)$$

So on

Estimating the iteration of the initial weights and the initial latent variable values starting from step 3, then from step 1 to step 3 is repeated until convergent, with convergence limits $((w_{ki}^* - w_{ki})/w_{ki}) \leq 10^{-5}$

$\hat{\eta}_i^* = \sum_i v_{ji}\xi_i$ with $v_{ji} = signcov\,(\eta_i, \xi_i)$

for i=1,2,…,m

$\hat{\eta}_i^* = v\eta_j + \sum_i v_{li}\xi_i$

with $v = signcov\,(\eta_l, \eta_i)$,

and

$v_{li} = signcov\,(\eta_l, \xi_i)$ for i=1,2,…,m

$$signcov(\eta, \xi) = \begin{cases} 1 \text{ if } \eta \text{ and } \xi \text{ associated} \\ 0 \text{ if } \eta \text{ and } \xi \text{ not associated} \end{cases} \qquad (2)$$

#Inside approximation

$$Z_j = \sum_{i \leftrightarrow j} v_{ij} Y_i \qquad (3)$$

#Outer Weight

Outer weights of reflective indicators :

$$\tilde{w}_{jk} = (Y_j'Y_j)^{-1}Y_j'X_{jk} \qquad (4)$$

Outer weights of formative :indicators

$$\tilde{w}_{jk} = (X_j'X_j)^{-1}X_j'Y_j \qquad (5)$$

#Outside approximation

$\hat{\xi}_j = \sum_{kj} \hat{w}_{kj} x_{kj}$ for k=1,…, s_j

and j=1,2,…,m

s_j = number of manifest variables block j-th (6)

$\hat{\eta}_i = \sum_{ki} \hat{w}_{ki} y_{ki}$ for k=1,…, r_i

And i=1,2,…,n

r_i = number of manifest variables block I-th (7)

Stage 2. Estimating the path coefficient with the ordinary least Square.

$$Y_j = \sum_{i \to j} \widehat{\beta_{ji}} Y_i$$
$$\beta_{ji} = (Y_i'Y_i)^{-1}Y_i'Y_j \qquad (8)$$

stage 3.compute the *Loadings*

$$\hat{\lambda}_{jk} = corr(X_{jk}, Y_j) \qquad (9)$$

III. DATA SOURCES

The population in this study were all students of class XI of senior high school (SMK) YPKK Sleman of Indonesia in the 2016/2017 Academic Year consisting of 5 classes and a total of 115 students. The research variable consists of the dependent variable which is a variable that is considered an observable variable and a predictor variable which is a latent variable. In this study as the dependent variable namely Learning Achievement for Fixed Assets Subjects (Y) is the level of student success in achieving goals seen from students' mastery of Fixed Assets subjects, thus producing mastery, knowledge, thinking skills and motor skills.

Latent Variable (LV) of Learning Motivation (X1) is the encouragement and driving force in students that lead to activities to do things in a direction to achieve a goal. Latent variable Parental Socioeconomic Status (X2) is the position of parents in the community that can be measured by the type and location of the house, family income, and several other criteria regarding family welfare. The economic situation of parents is closely related to children's learning. Latent Variable School Environment (X3) is all conditions in formal educational institutions including things that affect student behavior including the school's physical environment such as the campus environment, existing learning facilities and infrastructure, learning resources, learning media, and social environment which concerns students 'relationships with their peers, teachers and other school staff.

In detail to collect data from the predictor variables which are latent variables, the research instrument is designed which is derived from the indicators of latent variables into the question items in the questionnaire. In this study, the details are presented in Table 1, Table 2, and Table 3.

Table 1. indicators of latent variables of Learning Motivation

No	Indicators	Number item	Total
1	Diligently facing the Task	1,2,3*,4,5	5
2	Tenacious faces difficulties	6,7*,8,9	4
3	Showing interest in various problems for adults	10,11,12,13	4
4	More often work independently	14*,15,16	3
5	Quickly bored with routine tasks	17,18*	2
6	Can defend his opinion	19,20*,21	3
7	It's not easy to let go of things that are already believed	22,23,24,25	4
8	Happy to find and solve problems	26,27	2

The LV of learning motivation consists of 8 indicators broken down into 27 questions, in which there are 5 questions that are marked with asterisks as control questions.

Table 2. Indicators of the latent variable of parents socioeconomic status

No	Indicators	Number item	Total
1	Education	1,2	2
2	Income	3,4	2
3	Valuable property	5,6,7,8	4

4	Social power or position in the Community	9,10	2

The parents' socioeconomic status LV consists of 4 indicators broken down into 10 question points as in table 2.

Table 3. Indicators of latent variables in the school environment

No	Indicators	Number item	Total
1	Teaching method	1*,2,3	3
2	Curriculum	4,5	2
3	Relationship between teachers and students	6,7,8	3
4	Relationship among students	9,10,11*	3
5	School discipline	12,13*,14	3
6	Teaching tools	15*,16,17	3
7	School time	18,19*,20	3

The LV of the school environment consists of 7 indicators broken down into 20 question items with 5 questions given an asterisk as a control question.

IV. RESULT AND DISCUSSION

In this session an explanation will be made related to data description, interpretation of the results of the analysis which includes inner model, outer model and continued with the type of influences among the LV.

A. Data description

Based on the data of Learning Achievement of Fixed Assets Subjects obtained through documentation in the form of an average value of five times daily repetitions for one semester, the values of Mid Semester Tests, End of Semester Tests for class XI students of SMK YPKK 2 Sleman Academic Year 2016/2017, the maximum value is 94.9 and the minimum value is 44.4. Furthermore, an analysis was obtained with a mean value of 69, a median of 66.7, a mode of 51.60, and a standard deviation of 12.9.

Learning Motivation variable data is obtained through a questionnaire consisting of 25 statement items with 115 respondents. There are four alternative answers where the highest score is 4 and the lowest score is 1. Based on data analysis of Learning Motivation variables, the highest score can be obtained 97 and the lowest score is 58, with a Mean value of 72.9, a Median of 72, Mode of 70, and a Standard Deviation of 8.1. Variable Data on Socio-Economic Status of Parents was obtained through a questionnaire consisting of 9 statements with 115 respondents. There are 4 alternative answers where the highest score is 4 and the lowest score is 1. Based on the results of the data analysis of the Socio-Economic Status variable of Parents, the highest score can be obtained 30 and the lowest score is 10; with a Mean value of 16.9, a Median of 17, Mode of 15, and a Standard Deviation of 3.3. School environment variable data was obtained through a questionnaire consisting of 16 statements with 115 student respondents. There are 4 alternative answers where the highest score is 4 and the lowest score is 1. Based on the analysis of the School Environment data variable, the highest score can be obtained 62 and the lowest score is 40; with a Mean value of 51.6, a Median of 52, Mode of 54, and Standard Deviation of 4.9.

B. Inner model loading

The presence of latent variables (LV) that cannot be observed directly in a system that is modeled raises the indicator or question items as manifest variables. PLS analysis is able to measure the significance of each manifest variable for the LV constructed or reflected. The significance of each item is expressed in the form of a confidence interval.

Table 4. The loading value of each item questionnaire and 5% of the confidence interval

Item	Loading values	5% lower limit	5% upper limit
Learning Motivation variable			
V_1	07094	0.6146	0.780
V_2	0.5725	0.4204	0.678
V_3	0.5355	0.2590	0.680
V_4	0.6043	0.4549	0.712
V_5	0.4813	0.2296	0.648
V_6	0.7049	0.5973	0.789
V_7	0.4296	0.1746	0.636
V_8	0.6133	0.4896	0.724
V_9	0.4536	0.1464	0.630
V_{10}	0.6219	0.3709	0.746
V_{11}	0.5718	0.3458	0.704
V_{12}	0.5276	0.3668	0.671
V_{13}	0.6142	0.3902	0.735
V_{14}	0.5074	0.2603	0.648
Socio-Economic Status of Parents variable			
V_{26}	0.7116	0.2375	0.813
V_{27}	0.8068	0.1900	0.867
V_{28}	0.6117	0.1389	0.759
V_{29}	0.6233	-0.0438	0.767
V_{30}	0.1924	-0.2506	0.786
V_{31}	0.4346	0.0137	0.653
School environment variable			
V_{35}	0.5952	0.4207	0.713
V_{36}	0.6320	0.4341	0.732
V_{37}	0.4545	0.2340	0.605
V_{38}	0.1392	-0.1825	0.453
V_{39}	0.2881	0.0986	0.494
V_{40}	0.5179	0.2688	0.673
V_{41}	0.0906	-0.1134	0.419
V_{42}	0.5387	0.3779	0.656
V_{43}	0.6592	0.4561	0.749
V_{44}	0.3946	0.1204	0.586
V_{45}	0.6489	0.4235	0.773
V_{46}	0.4715	0.2764	0.630
V_{47}	0.6922	0.5225	0.773

V_{48}	0.6554	0.4843	0.780
V_{49}	0.5331	0.3176	0.708
V_{50}	0.2672	0.0496	0.494
Learning Achievement variable			
V_{51}	1.000	1.000	1.000

The first column of table 4 states the notation of each questionnaire item from each LV. The second column states the amount of loading values of the corresponding items in the first column. The 5% confidence limit located in column 3 and column 4 serves to test the significance of the questionnaire items against the corresponding LV. If the confidence interval contains a value of 0 then the item does not have a significant contribution at the 5% level of significance. Based on table 4 it can be seen that many significant items, while insignificant items can be discarded or added new items that are assumed to contribute to explaining LV.

C. Coefficient of outer model and relationship among Latent variables

In this study several hypotheses will be confirmed which would be very complicated if analyzed with multiple regression models using OLS parameter estimators. Because the hypothesis that will be proven to form a structural model is a combination of a linear regression model and path analysis, the PLS estimation method is applied in order to produce simultaneous parameter estimators. There are 5 hypotheses to be proven, i.e

1. Does learning motivation (LM) affect the school environment (SE)
2. Does parental socioeconomic status (SS) affect the school environment (SE)
3. Does the school environment (SE) affect academic achievement (AC)
4. Does parental socioeconomic status (SS) affect academic achievement (AC)
5. Does learning motivation (LM) affect academic achievement (AC)

Table 5. Path coefficient and statistic values

Path direction	Path coefficient	t-statistic	p- value
LM→ SE	0.473	5.91	0.000^{s}
SS→ SE	-0.227	-2.83	0.006^{s}
LM→ AC	0.270	2.91	0.004^{s}
SS→ AC	0.249	2.98	0.003^{s}
SE→ AC	0.320	3.36	0.001^{s}
*s : significant, ns : not significant			
The R^2 value of			
SE	0.283		
AC	0.277		
Total	$Q^2 = 0.4816$		

Table 5 explains the coefficient values of a simple linear model that represents the form of the relationship between two causal variables, and also the p-value that reflects the significance of the coefficient. Based on the p-value in table 5 it can be seen that all coefficients are significant which all predictors have a significant influence on the dependent variable. In this study it can be proven that the 5 hypotheses above are proven..

In addition, excellence in PLS analysis can also explore various types of influence between LV relationships that are partially possible to find either in regression or path analysis.

Table 6. Exploration of various types of influences produced by PLS

Path direction	The effect of			Contribution
	Direct	**Indirect**	**Total**	
LM→ SE→ AC	0.270	0.151	0.421	0.1772 (17.72%)
SS→ SE→ AC	0.249	-0.072	0.177	0.0313 (3.13%)

The interpretation of table 6 is the learning motivation variable (LM) has a direct effect on academic achievement (AC) of 0.270, the indirect effect of learning motivation variable (LM) on academic achievement (AC) through the school environment variable (SE) of 0.151. The total effect of the learning motivation variable (LM) on academic achievement (AC) is 0.421. The contribution of learning motivation variable (LM) to academic achievement (AC) is 17.72% which is the multiplication of the direct influence of learning motivation (LM) on the school environment (SE) and the direct influence of the school environment (SE) on academic achievement (AC).

V. CONCLUSION

Based on the results obtained in this study it can be seen that the relationship model that occurs in the dependent variable academic achievement (AC) and predictor variables consist of learning motivation (LM), parents' socioeconomic status (SS), school environment (SE)) is not just just a simple linear regression, but is a combination of simple linear regression and path analysis known as the structural equation model (SEM). Questionnaire items from each latent variable were successfully confirmed and it was proven that the questionnaire items from each latent variable significantly contributed to reflecting or constructing the latent variable. All predictors individually have a significant effect on learning achievement (AC). The variable of learning motivation (LM) and the socioeconomic status of parents (SS) also significantly influence the school environment variable (SE) at 5% significance level. Learning motivation (LM) has a total effect on learning achievement (AC) of 42.1% and has a contribution to academic achievement (AC) of 17.72%. Parental socioeconomic status variable (SS) has a total effect on academic achievement of 17.7% and contributes to academic achievement (AC) of 3.13%.

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